Finding Solutions

Using Machine-Learning to Dynamically Generate Operationally Acceptable Strategic Reroute Options

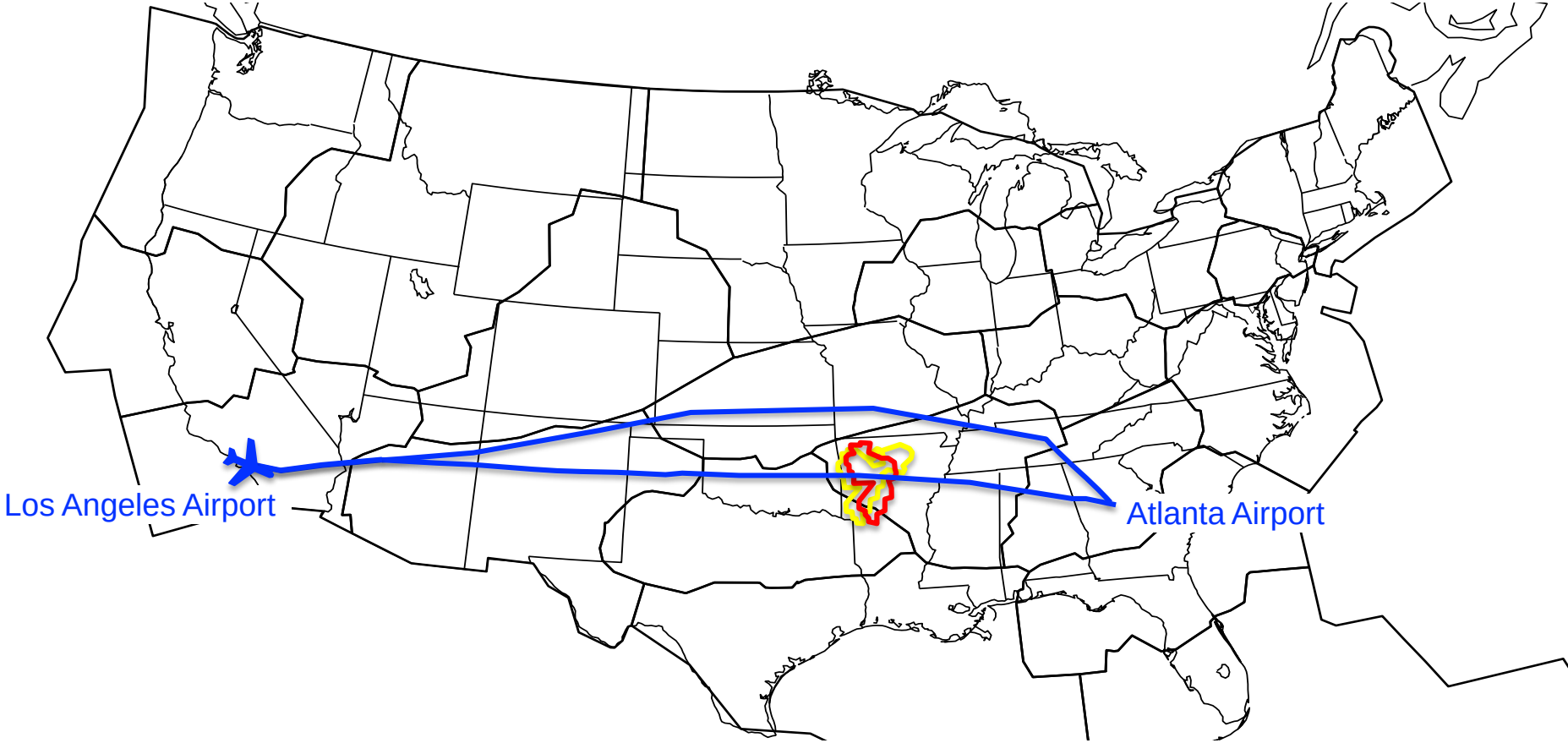
Antony Evans (formerly Crown Consulting, Inc)*

Paul Lee (NASA Ames)

* Now working for Airbus

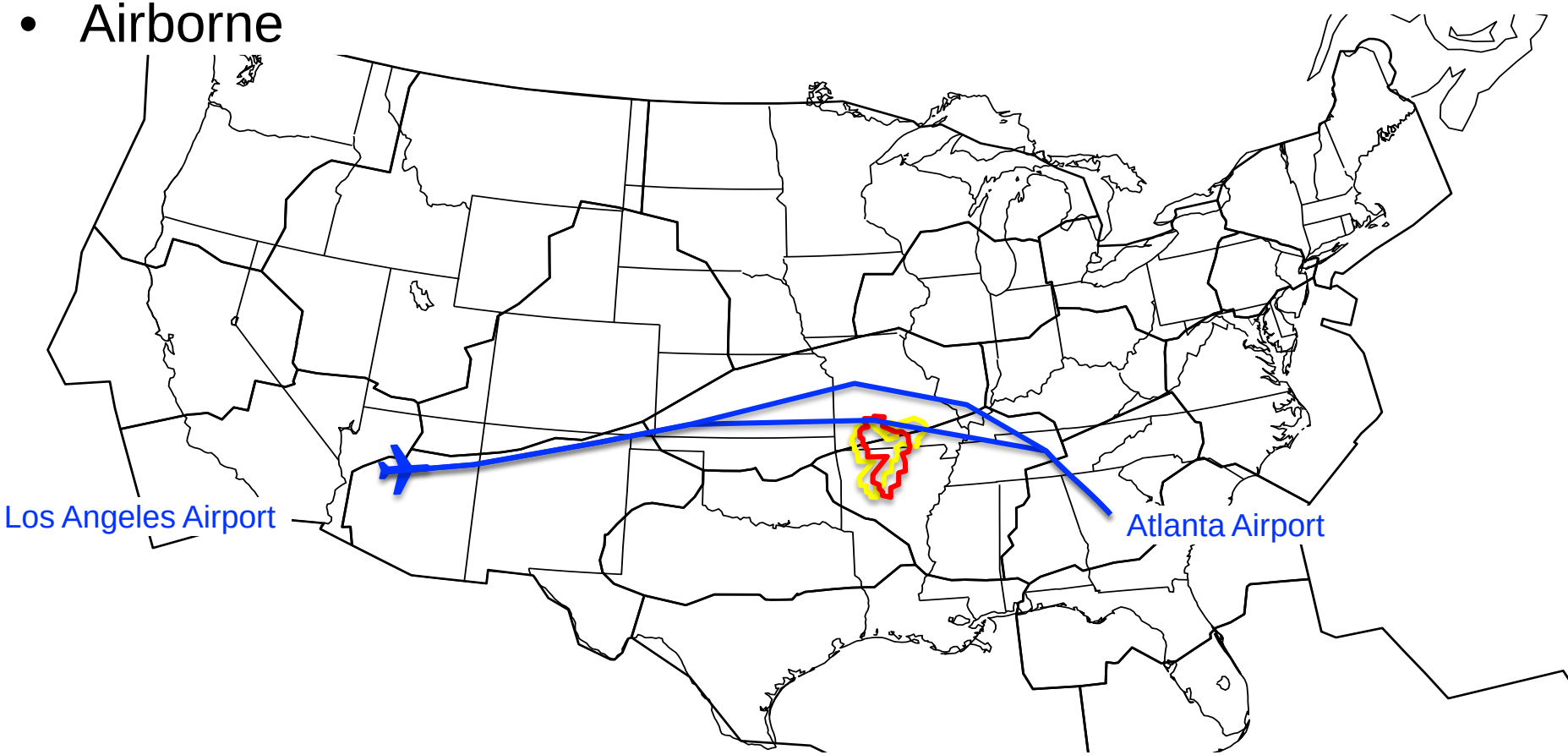
Strategic Rerouting

- Hours before departure
- Pre-departure



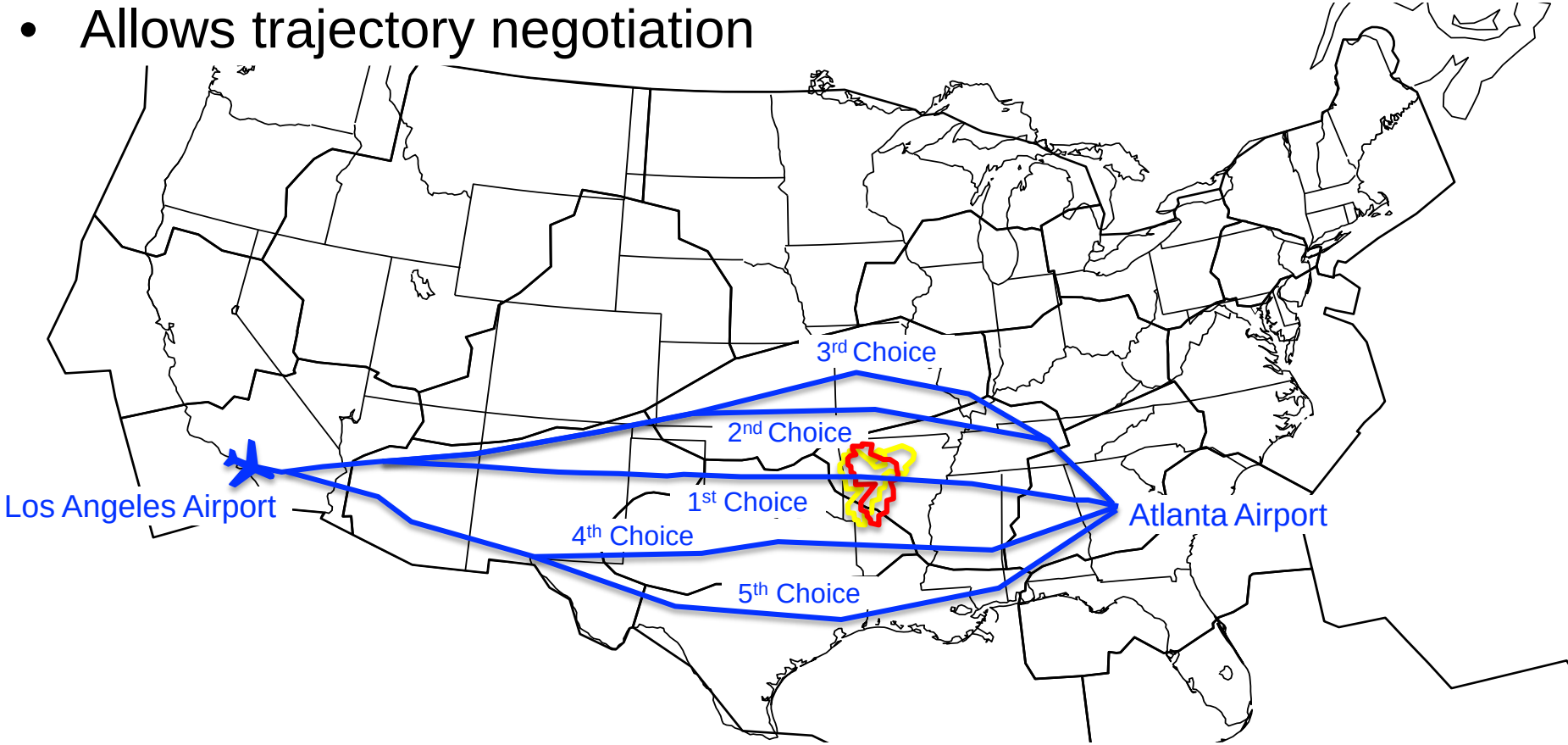
Strategic Rerouting

- Hours before departure
- Pre-departure
- Airborne



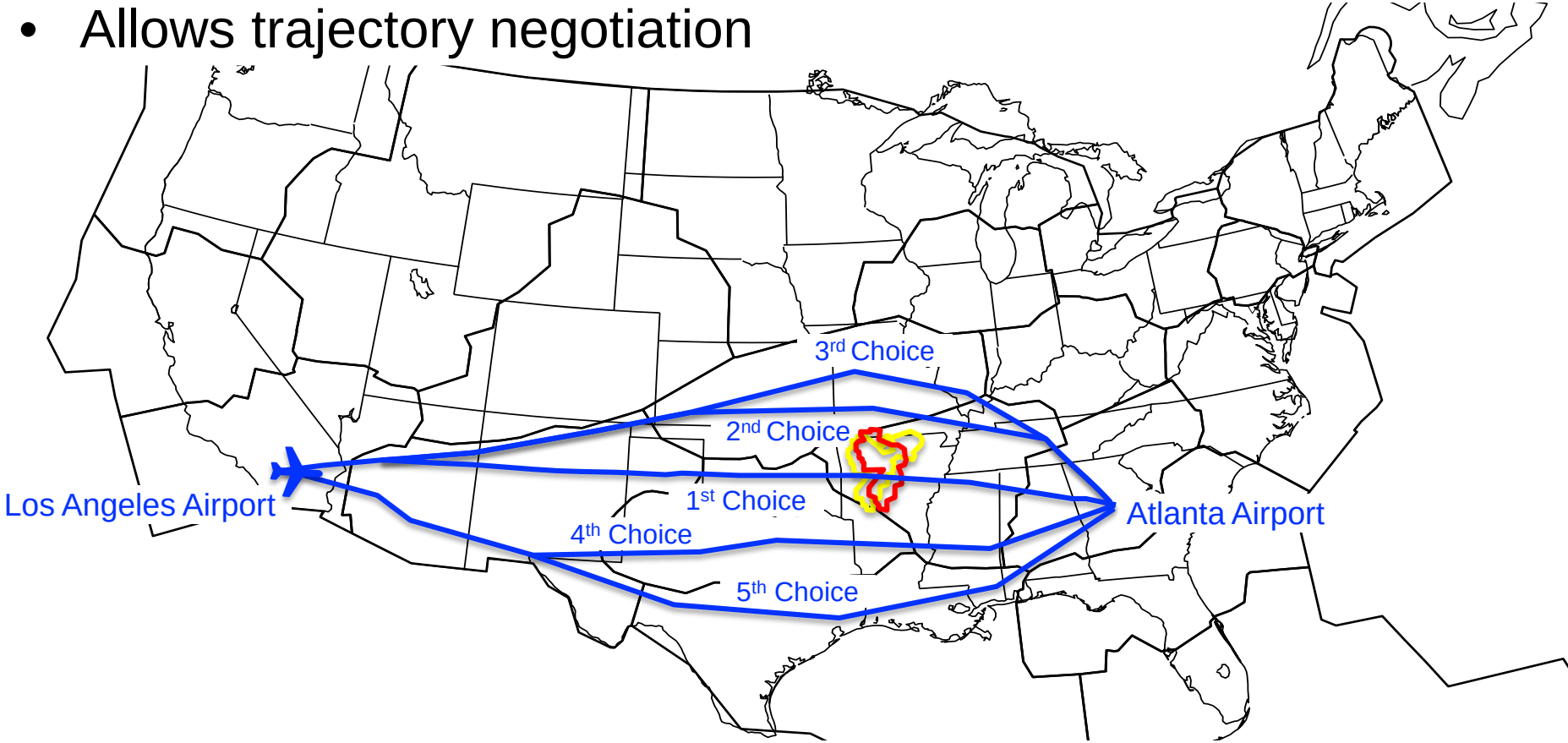
Trajectory Option Set (TOS)

- Preference-weighted set of alternative routes submitted by flight operators
- Allows trajectory negotiation



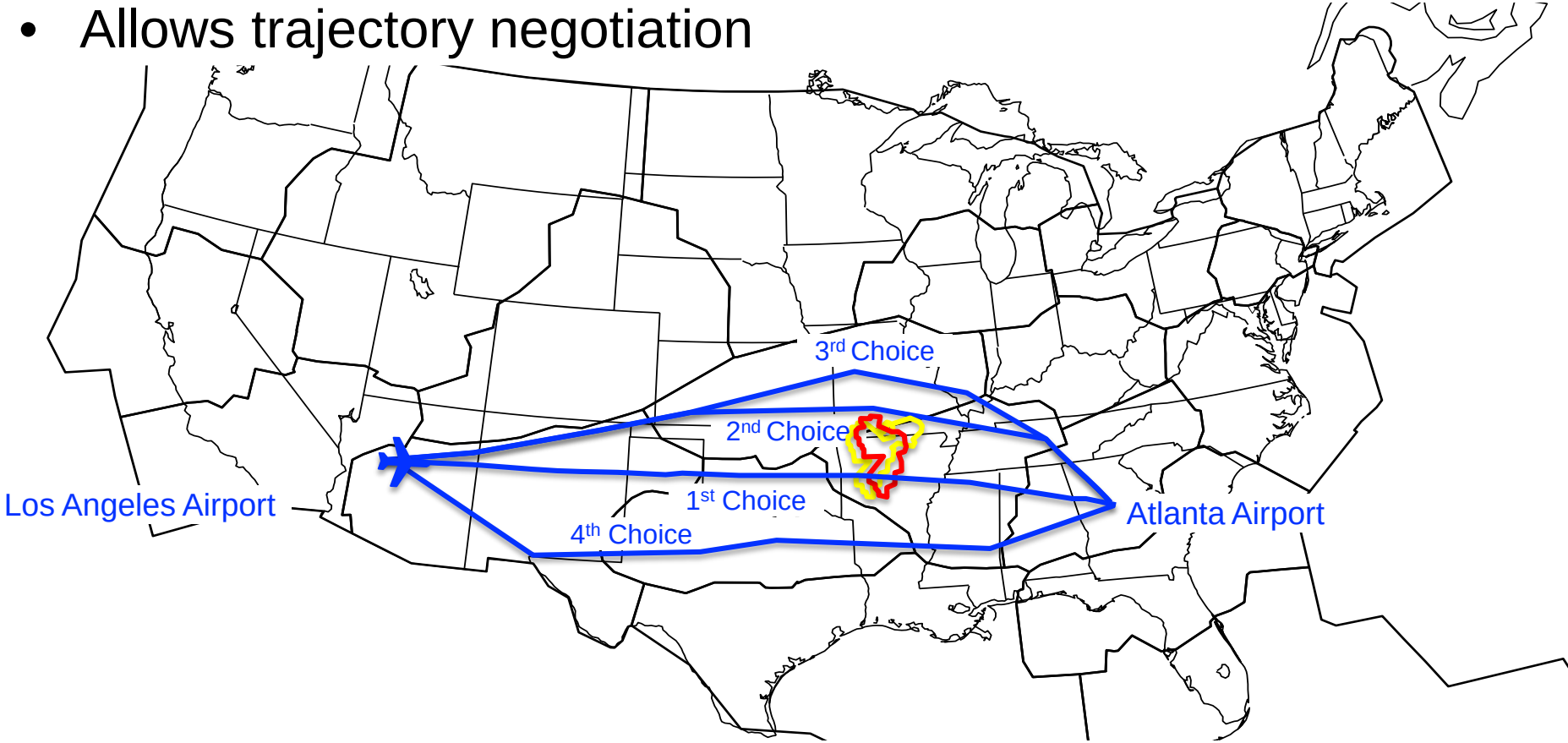
Trajectory Option Set (TOS)

- Preference-weighted set of alternative routes submitted by flight operators
- Allows trajectory negotiation



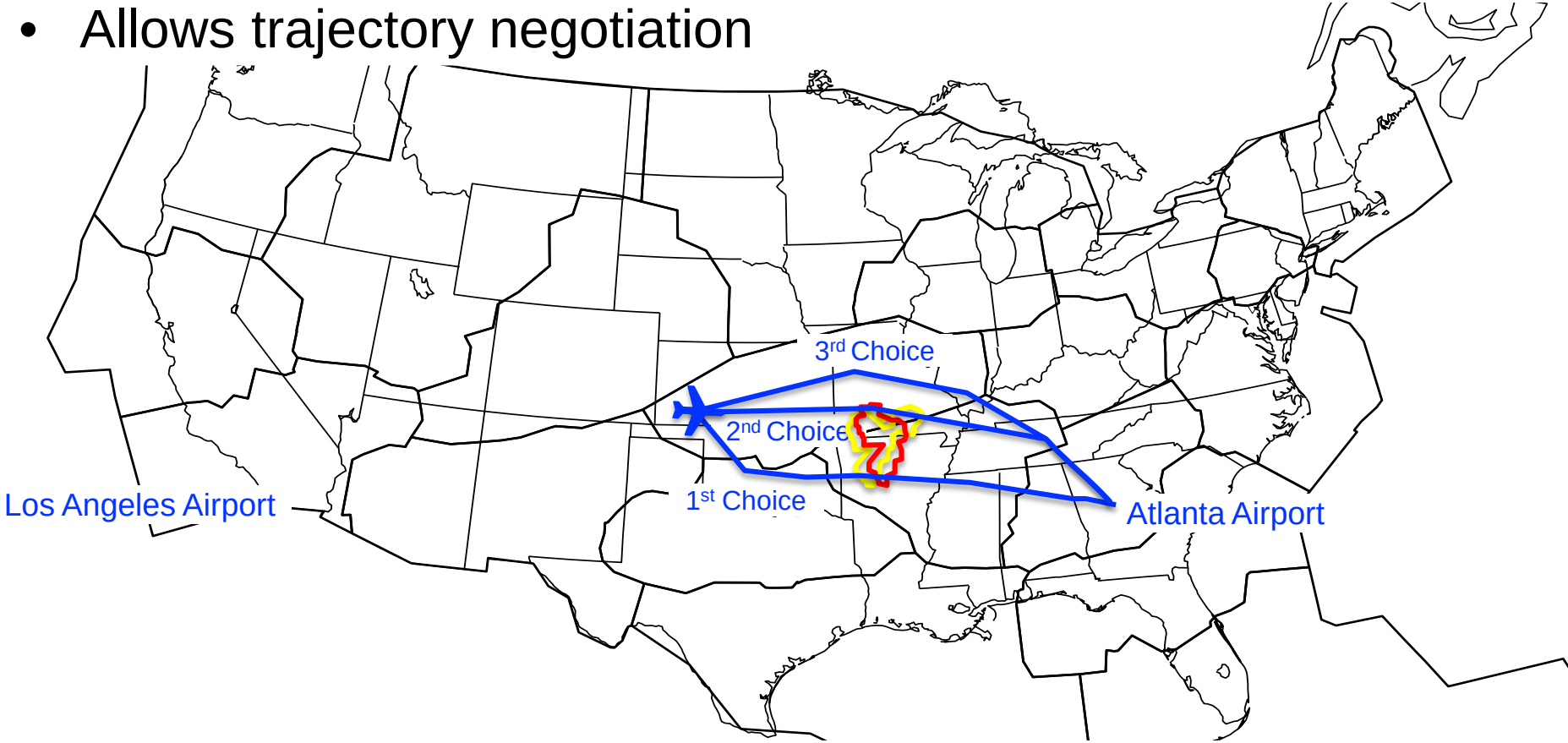
Trajectory Option Set (TOS)

- Preference-weighted set of alternative routes submitted by flight operators
- Allows trajectory negotiation



Trajectory Option Set (TOS)

- Preference-weighted set of alternative routes submitted by flight operators
- Allows trajectory negotiation



Trajectory Negotiation

- Advantages
  - Enables flight operators to tailor trajectories based on preferences
  - Enables better utilization of available airspace resources
    - Reducing delay & increasing throughput
  - Increases predictability
- Barriers
  - Routes must be operationally acceptable

Can we automatically generate a TOS with high probability of operational acceptance?

Literature Review

Hall, W., Hunter, G., “Trajectory Optimization and the Clearable Route Network,” 2018.

- Commercial TOS generators under development, accounting for historical usage

Idris H., *et al.*, “Assessment of Air Traffic Controller Acceptability of Aircrew Route Change Requests,” 2017.

- Studies completed on operational acceptability

Taylor, C., Wanke, C., “Dynamically Generating Operationally Acceptable Route Alternatives Using Simulated Annealing,” 2012.

- Models generating strategic routes using optimization, constrained to meet criteria that make it operationally acceptable

Evans, A.D., Lee, P., “Predicting the Operational Acceptance of Route Advisories,” 2017.

- Previous NASA work uses machine learning to predict operational acceptability of airborne reroute requests

Objective

Automatically generate routes that have high probability of operational acceptance

Method: Use machine learning to train predictors on operational acceptance of strategic routes

Approach to TOS Generation

1. Identify available trajectory options
   - Based on historical routes

2. Down-select trajectory options
   - Using route clustering
   - Defines set of geographically distinct routes

3. Predict operational acceptability
   - Using machine learning algorithms
   - Given static and dynamic conditions

4. Select TOS
   - Based on location of constraint and probability of trajectory acceptance by ATC

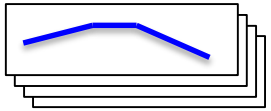
1. Identify Available Trajectory Options

Historical Usage

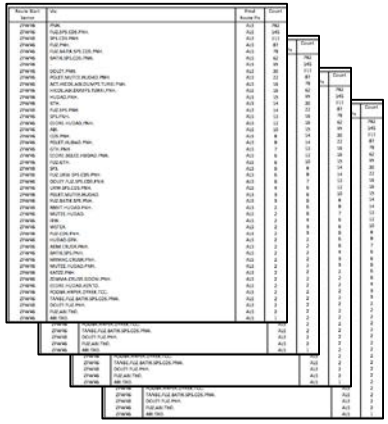
Flight Data

April 2015 | May 2015 | June 2015

Flight Plans, Flight Plan Amendments



Database of Trajectory Options



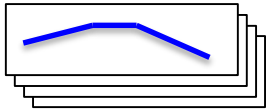
1. Identify Available Trajectory Options

Historical Usage

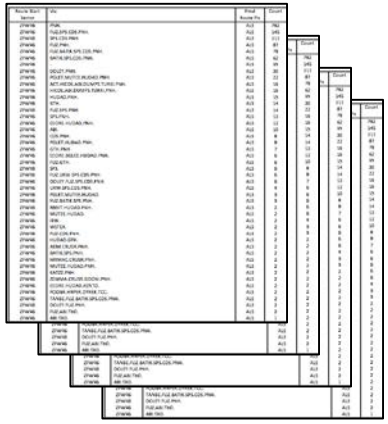
Flight Data

April 2015 | May 2015 | June 2015

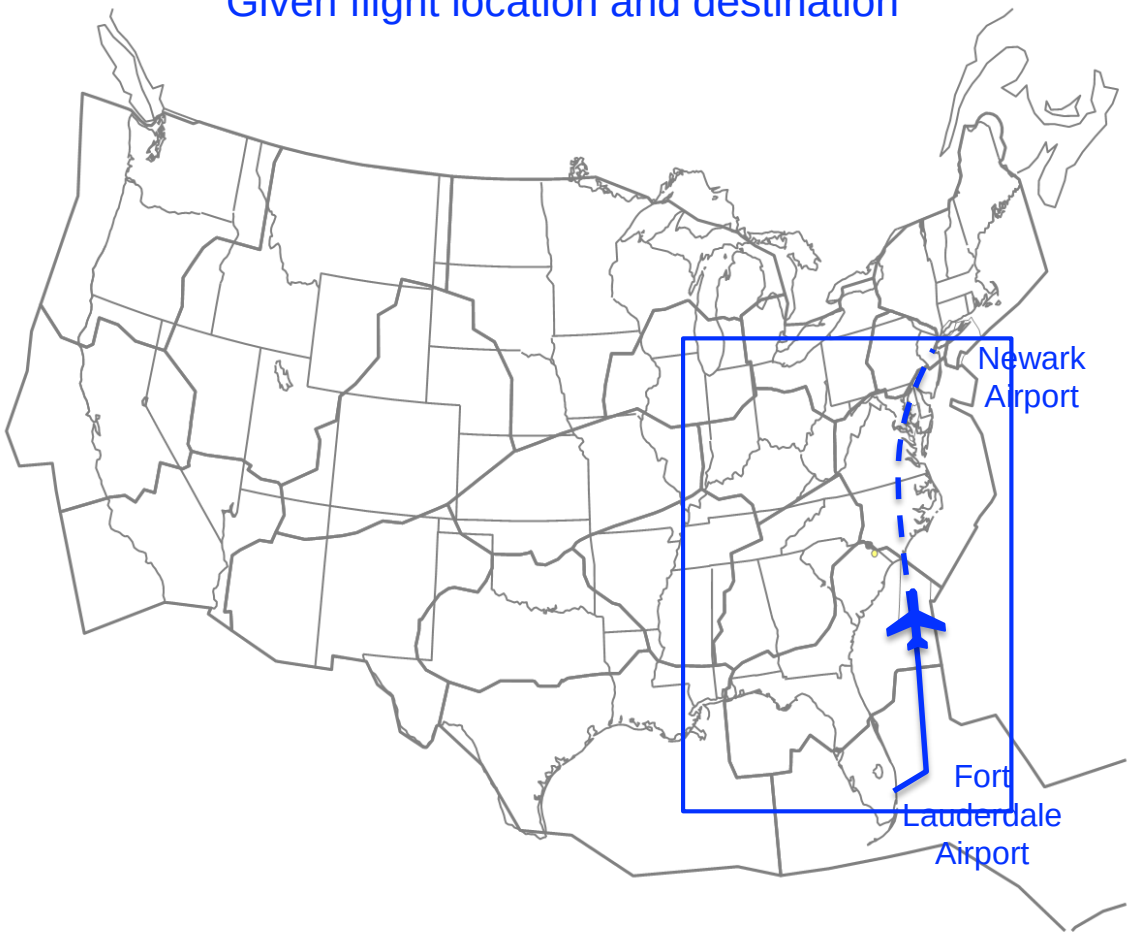
Flight Plans, Flight Plan Amendments



Database of Trajectory Options



Given flight location and destination



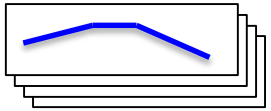
1. Identify Available Trajectory Options

Historical Usage

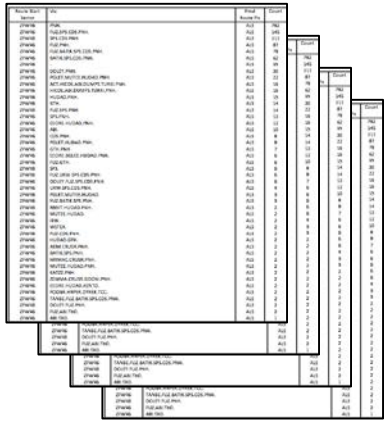
Flight Data

April 2015 | May 2015 | June 2015

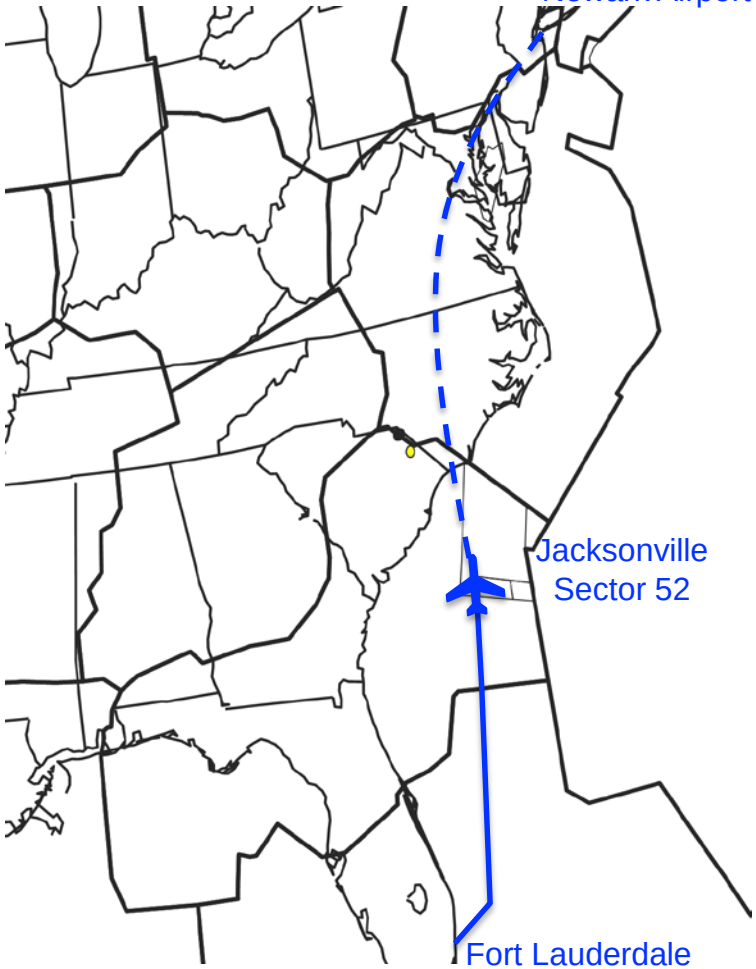
Flight Plans, Flight Plan Amendments



Database of Trajectory Options



Given flight location and destination



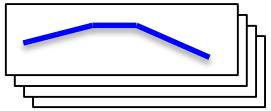
1. Identify Available Trajectory Options

Historical Usage

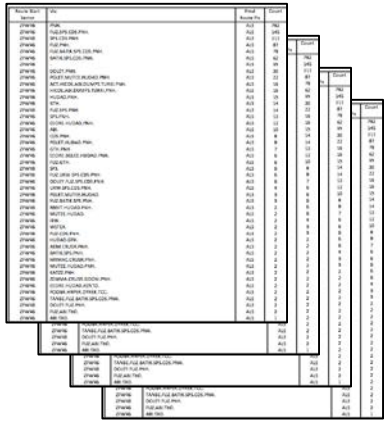
Flight Data

April 2015 | May 2015 | June 2015

Flight Plans, Flight Plan Amendments

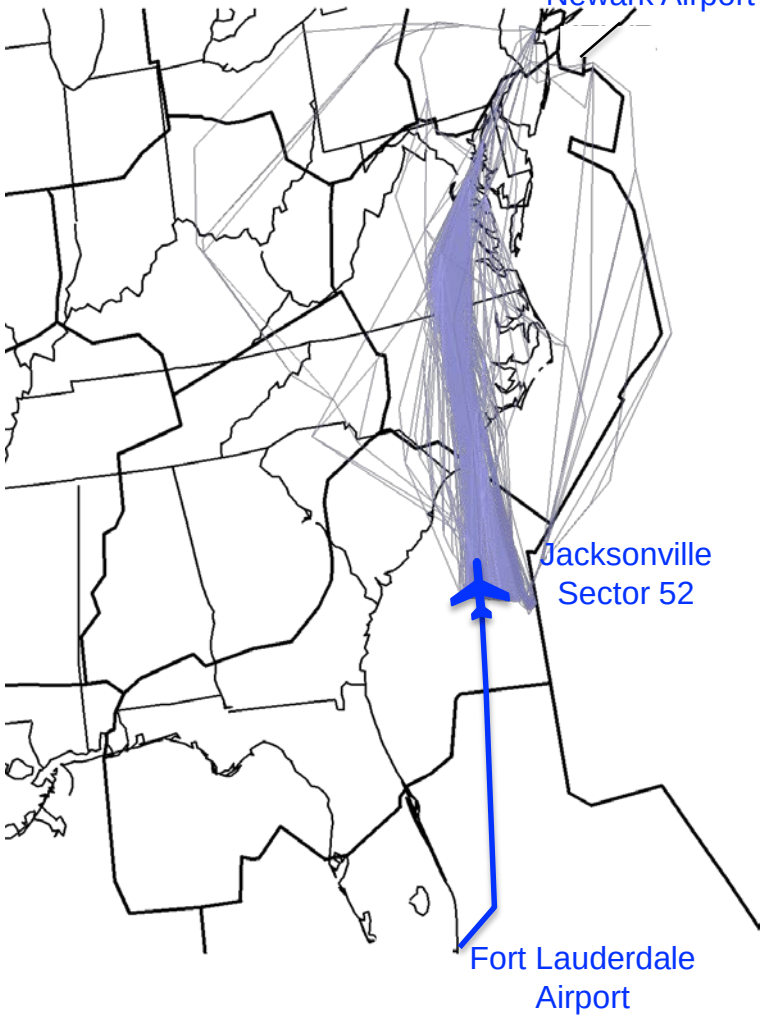


Database of Trajectory Options



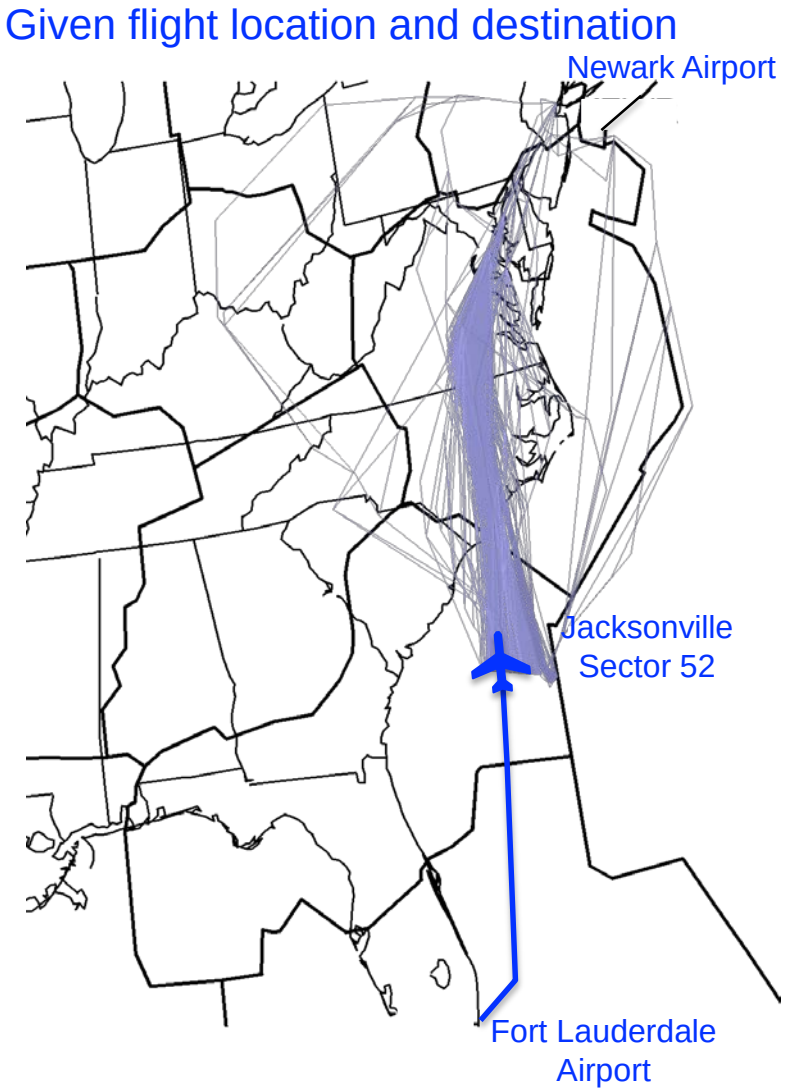
Historical Trajectories

Given flight location and destination



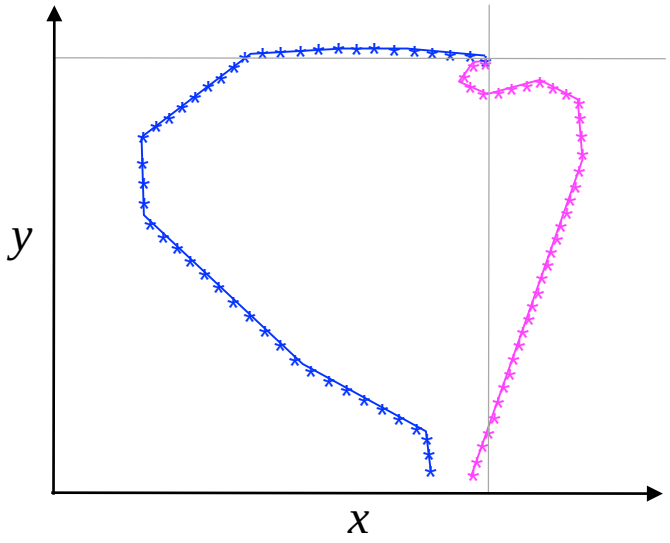
2. Down-Select Trajectory Options

- Apply Hierarchical clustering
- Dissimilarity metric calculated as Euclidean distance between trajectories
  - Each trajectory represented by a fixed length vector
  - Linear interpolation of 2D spatial position for 200 evenly spaced points



2. Down-Select Trajectory Options

- Apply Hierarchical clustering
- Dissimilarity metric calculated as Euclidean distance between trajectories
  - Each trajectory represented by a fixed length vector
  - Linear interpolation of 2D spatial position for 200 evenly spaced points



$$tr_i = (x_{i1}, y_{i1}, x_{i2}, y_{i2}, \dots, x_{iN}, y_{iN})$$
$$tr_j = (x_{j1}, y_{j1}, x_{j2}, y_{j2}, \dots, x_{jN}, y_{jN})$$
$$\dots$$
$$d_{ij} = \sqrt{\begin{matrix}(x_{i1} - x_{j1})^2 + (y_{i1} - y_{j1})^2 + \cdots \\ +(x_{iN} - x_{jN})^2 + (y_{iN} - y_{jN})^2\end{matrix}}$$
$$\dots$$

2. Down-Select Trajectory Options

- Apply Hierarchical clustering
- Dissimilarity metric calculated as Euclidean distance between trajectories
- Number of clusters identified based on maximizing avg. Silhouette score

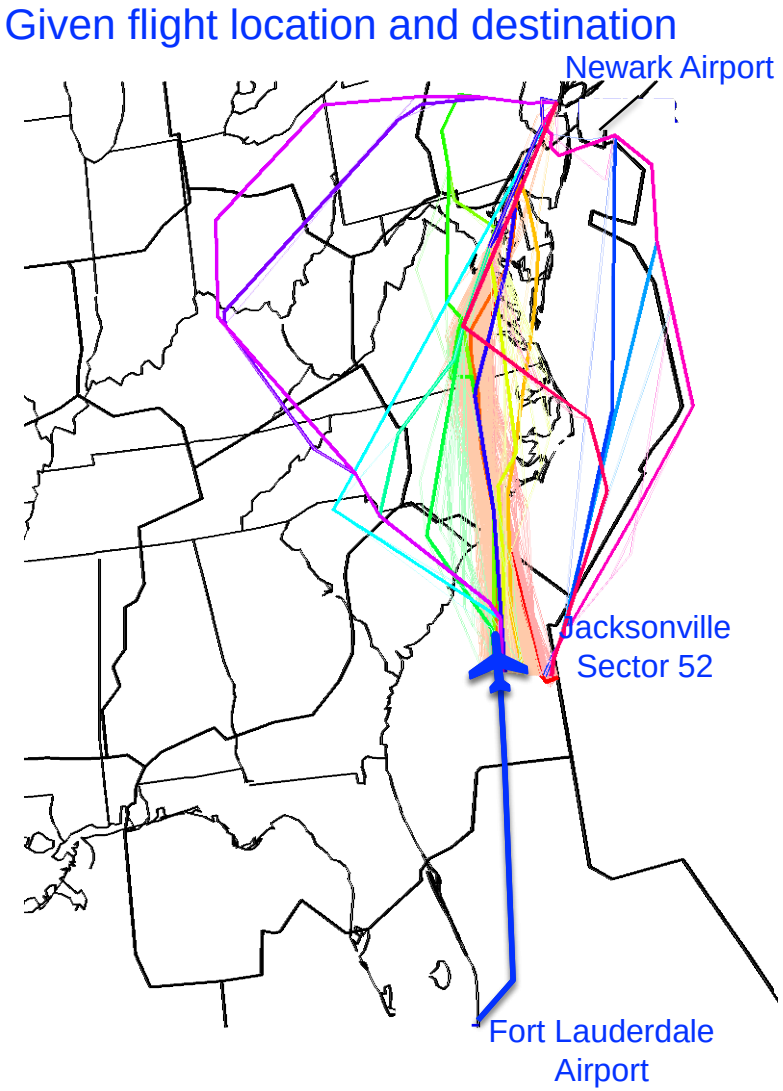
$$S = \frac{min(intercluster\ dist.) - intracluster\ dist.}{max(min(intercluster\ dist.), intracluster\ dist.)}$$

$$\bar{S} = \frac{1}{N_r}\sum_{1}^{N_r} S_i$$

- Minimum number of clusters set to 15

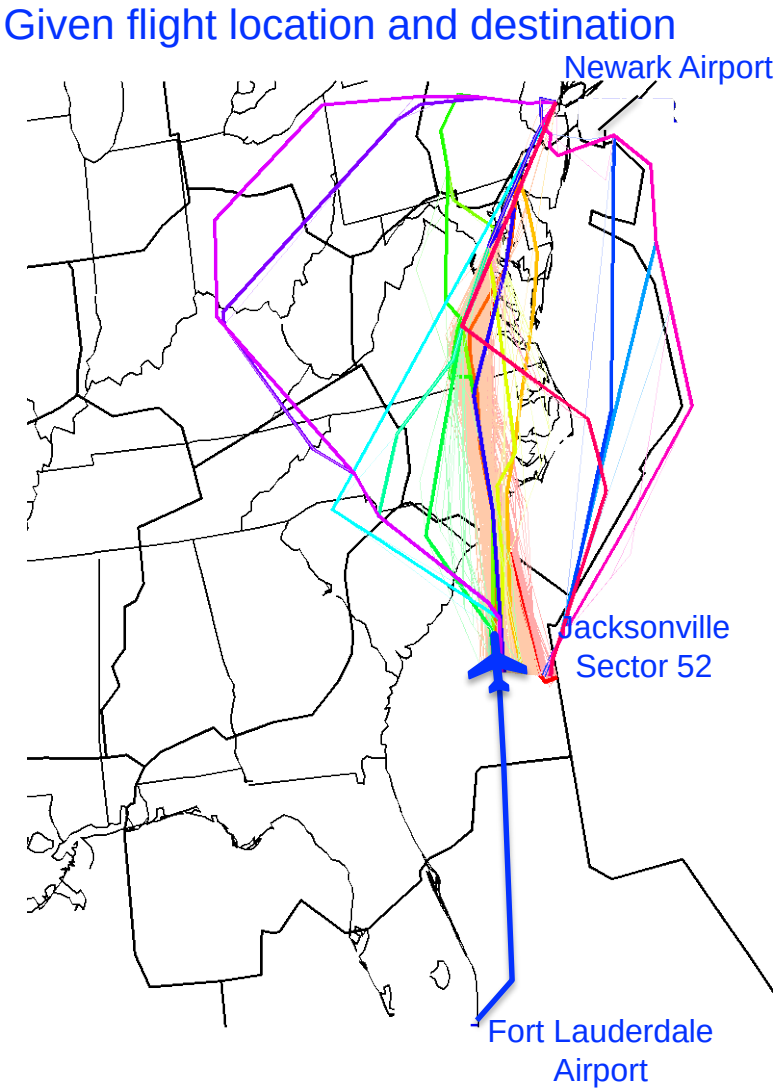
2. Down-Select Trajectory Options

- Apply Hierarchical clustering
- Dissimilarity metric calculated as Euclidean distance between trajectories
- Number of clusters identified based on maximizing avg. Silhouette score
  - For flight from Jacksonville Sector 52 to Newark Airport: 16 clusters
- Most commonly flown trajectory in each cluster identified for further analysis



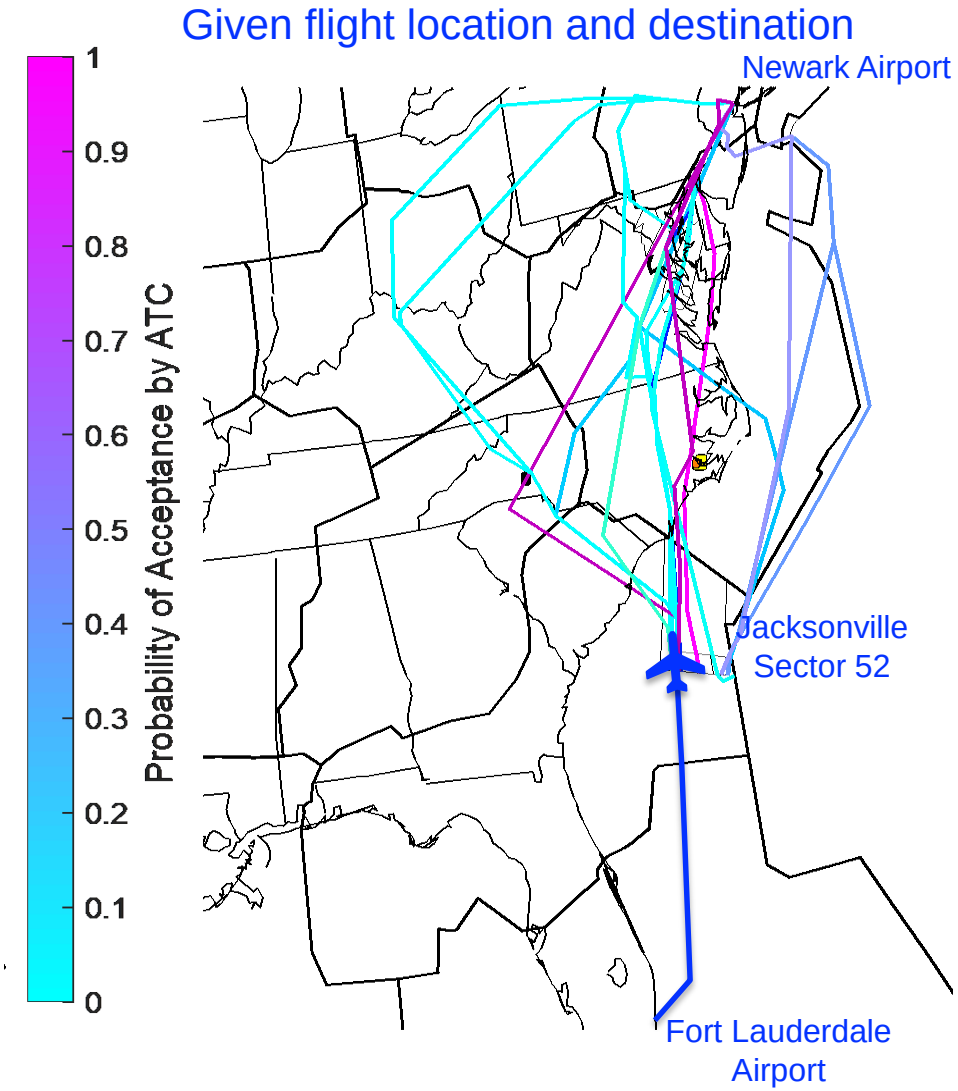
3. Predict Operational Acceptability

- Train machine learning algorithms on historical flight plan amendment data
  - Based on static and dynamic conditions impacting flight
- Select algorithm based on predictive performance using cross validation
- Apply chosen algorithm to predict operational acceptance for down-selected trajectory options



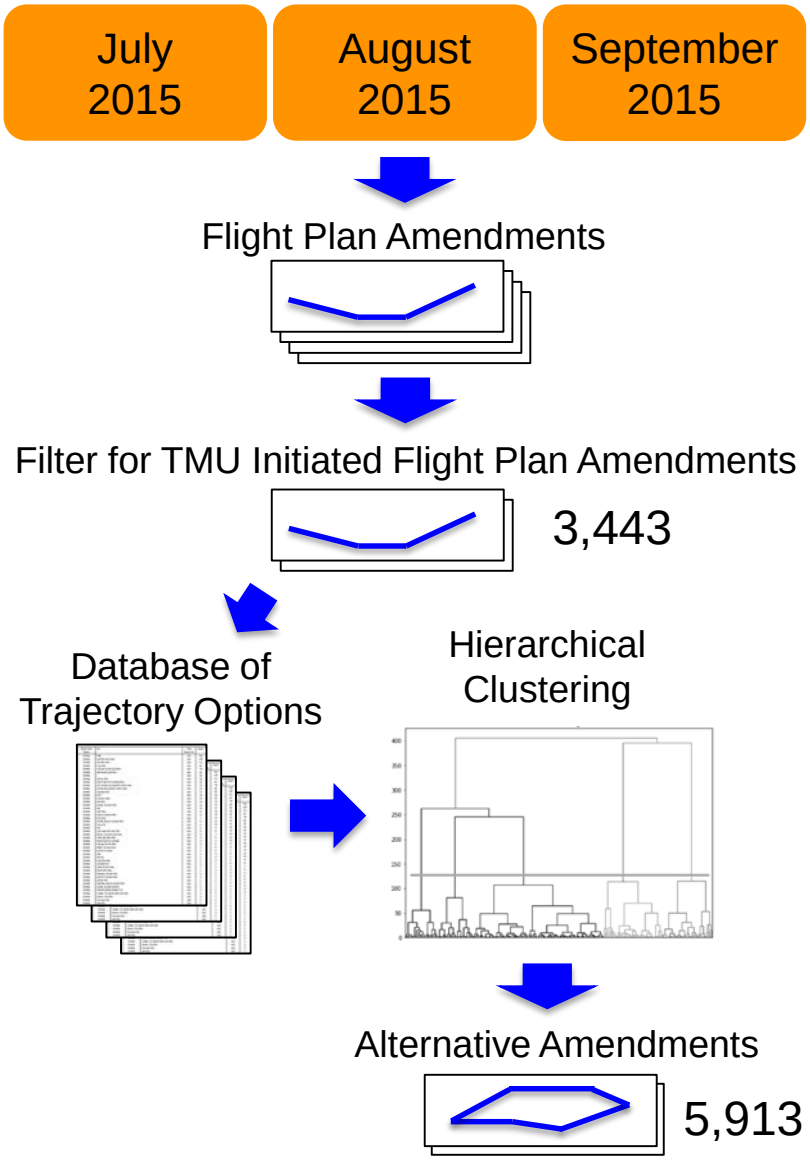
3. Predict Operational Acceptability

- Train machine learning algorithms on historical flight plan amendment data
  - Based on static and dynamic conditions impacting flight
- Select algorithm based on predictive performance using cross validation
- Apply chosen algorithm to predict operational acceptance for down-selected trajectory options



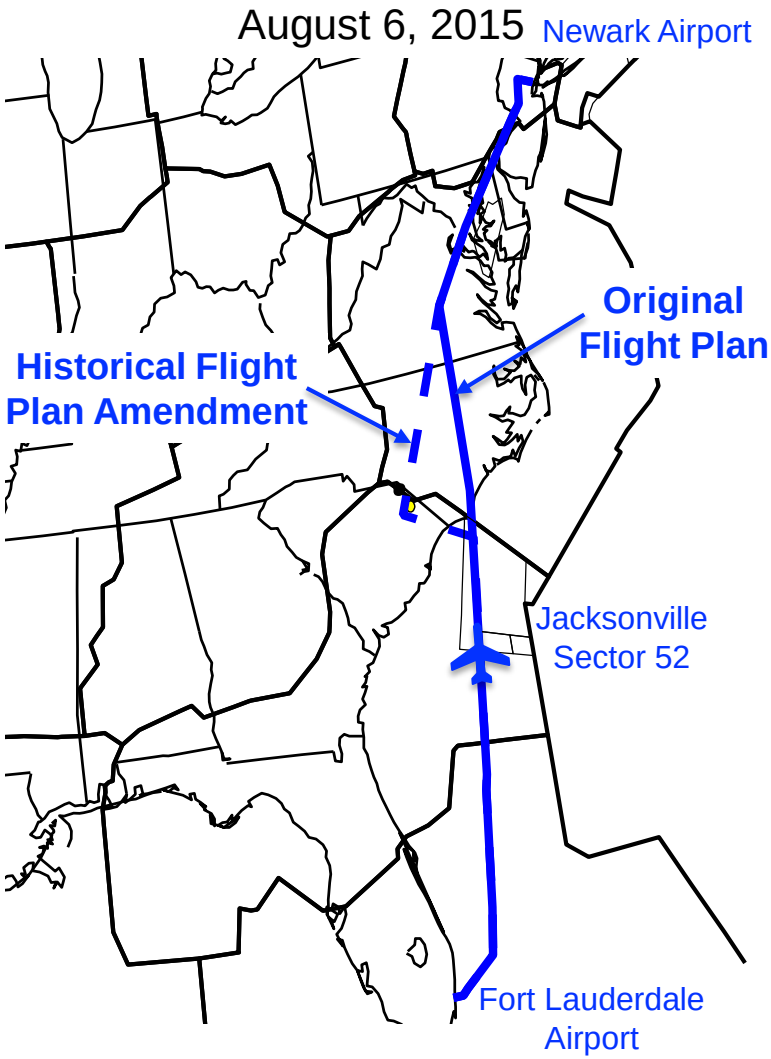
Training Data

- Positive class: Strategic historical flight plan amendments
  - Initiated by Traffic Management Unit (TMU)
  - Filter for amendments:
    - Through multiple Center facilities
    - Excluding direct routings
- Negative class: Generated artificially
  - Potential alternative amendments identified and assumed unacceptable
  - Identified using historical data and clustering



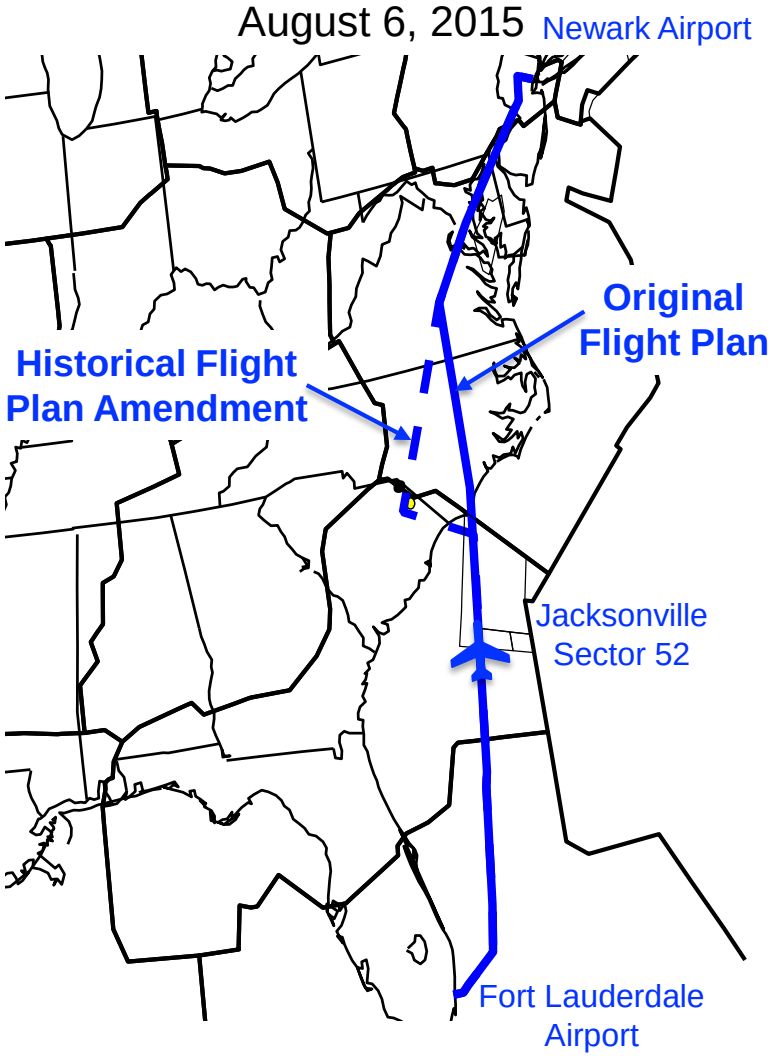
Features

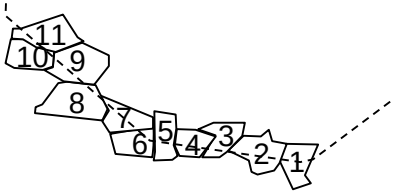
- Static features
  - Historical usage
  - Relative flight duration
- Dynamic features
  - Imbalance between demand and capacity



Features

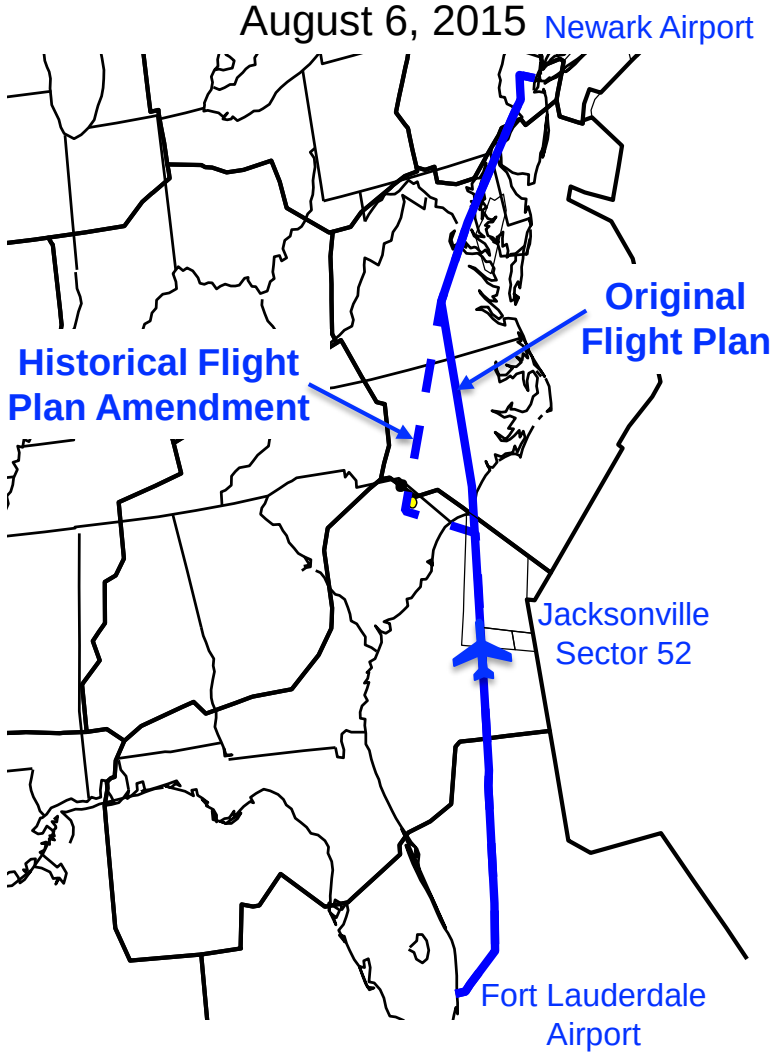
1. Historical Usage
   - Count of historical usage
   - Count as reroute
   - Full trajectory
   - Minimum across waypoint pairs
   - Difference in counts between original route and amendment

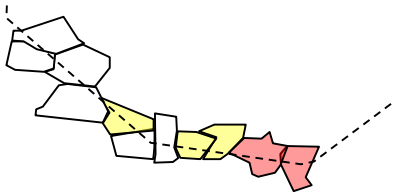




Features

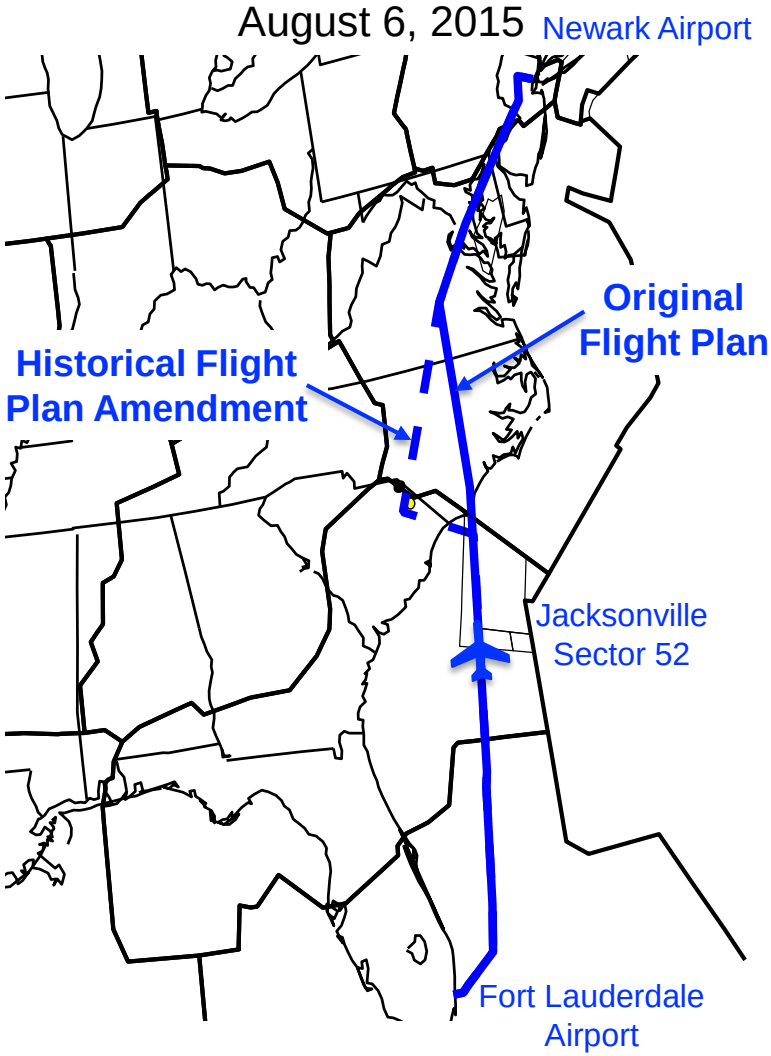
2. Flight Duration
   - Flight duration from amendment to destination
   - Difference in amendment duration relative to original flight plan
   - Number of sectors between amendment and destination
   - Difference in number of sectors between amendment and destination relative to original flight plan

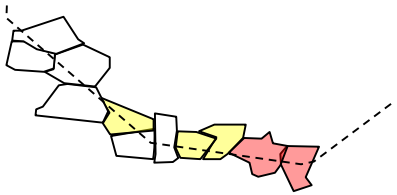




Features

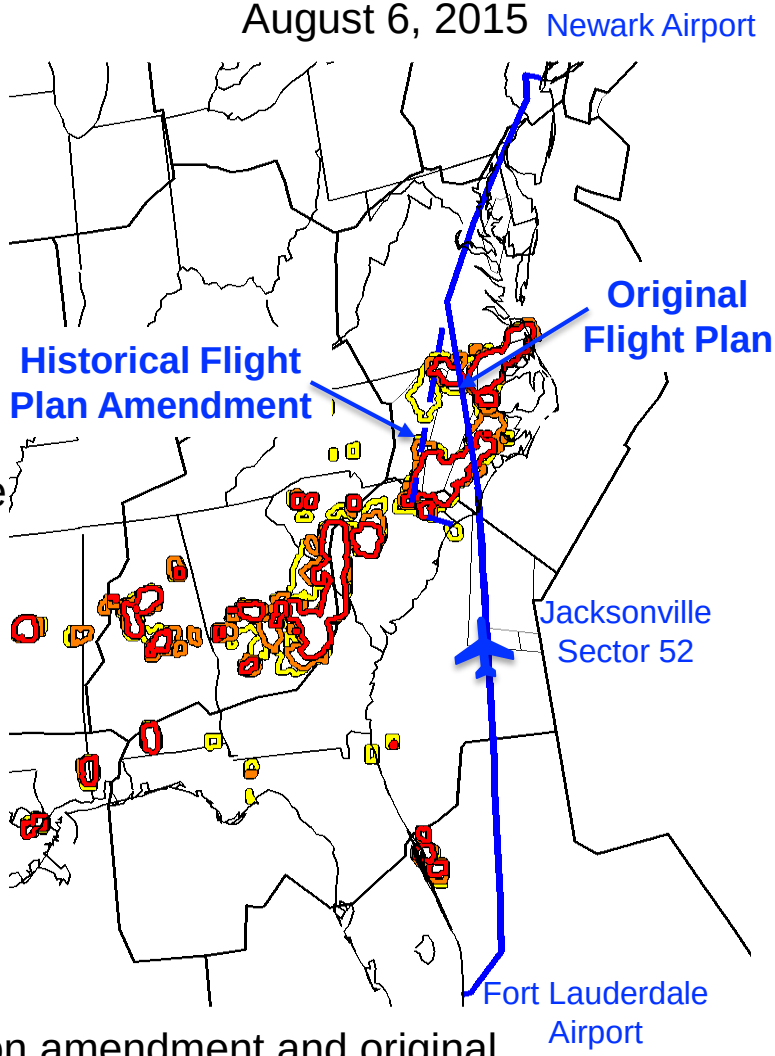
3. Demand to Capacity Imbalance
   - Projected demand calculated using NASA Future ATM Concepts Evaluation Tool (FACET)
   - Capacity defined by sector Monitor Alert Capacity and weather impact





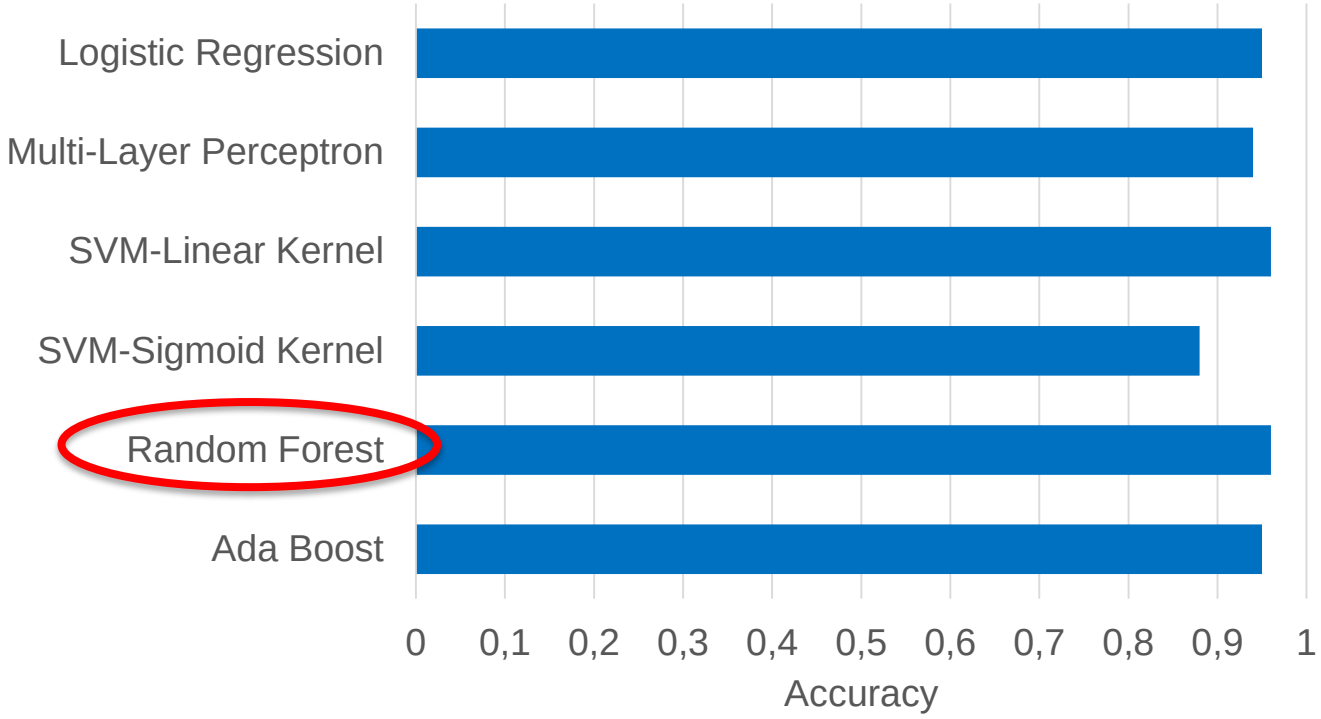
Features

3. Demand to Capacity Imbalance
   - Projected demand calculated using NASA Future ATM Concepts Evaluation Tool (FACET)
   - Capacity defined by sector Monitor Alert Capacity and weather impact
     - Forecast weather impact based on percentage overlap between sector and Convective Weather Avoidance Model (CWAM) polygons
     - 60%, 70% and 80% probability of deviation CWAM polygons used
   - Multiple metrics calculated:
     - Average demand/capacity
     - Maximum demand/capacity
     - Number of sectors over capacity
     - Whether any sector was over capacity
     - Difference between sum of demand/capacity on amendment and original

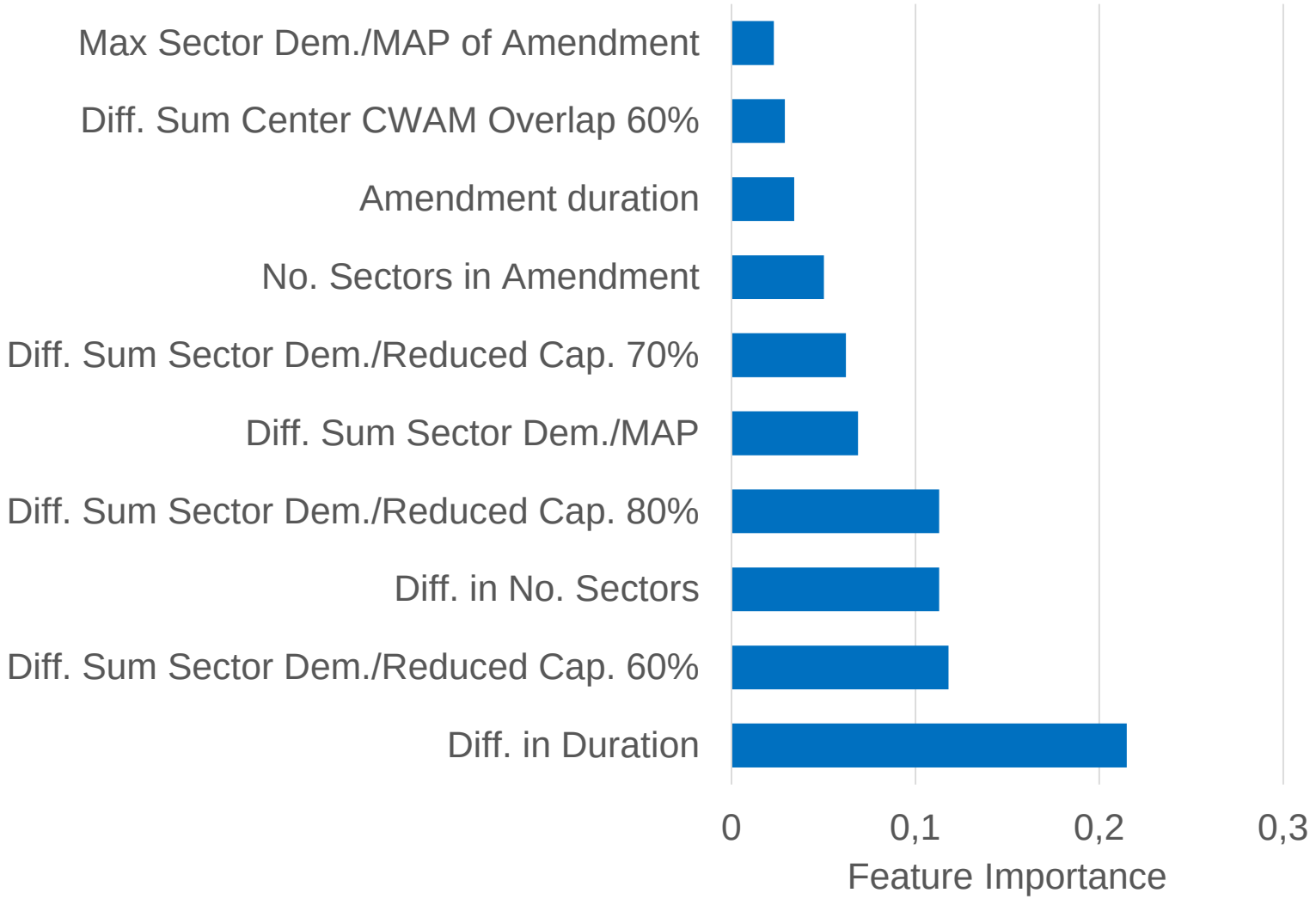


Model Selection

- Model performance estimated using 10-fold cross validation
- 9,356 observations: 36.8% positive, 63.2% negative
- Synthetic Minority Over-Sampling Technique (SMOTE) applied to balance dataset

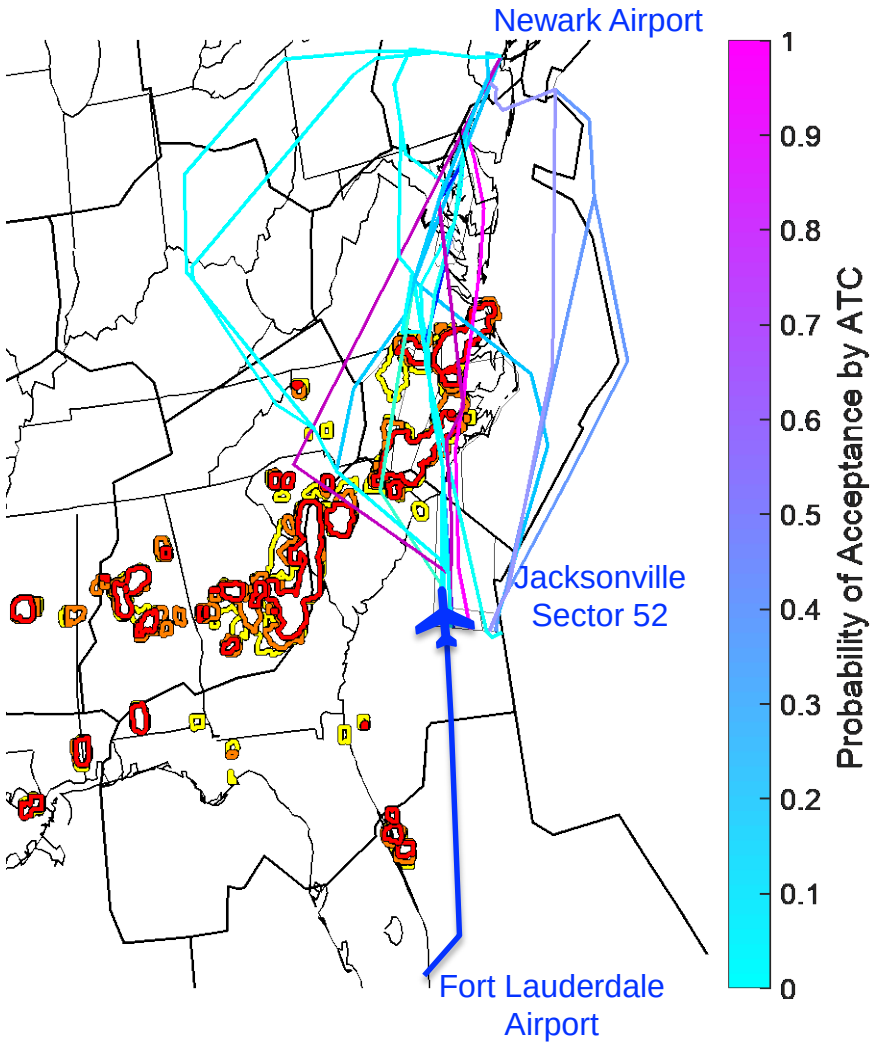


Feature Importance



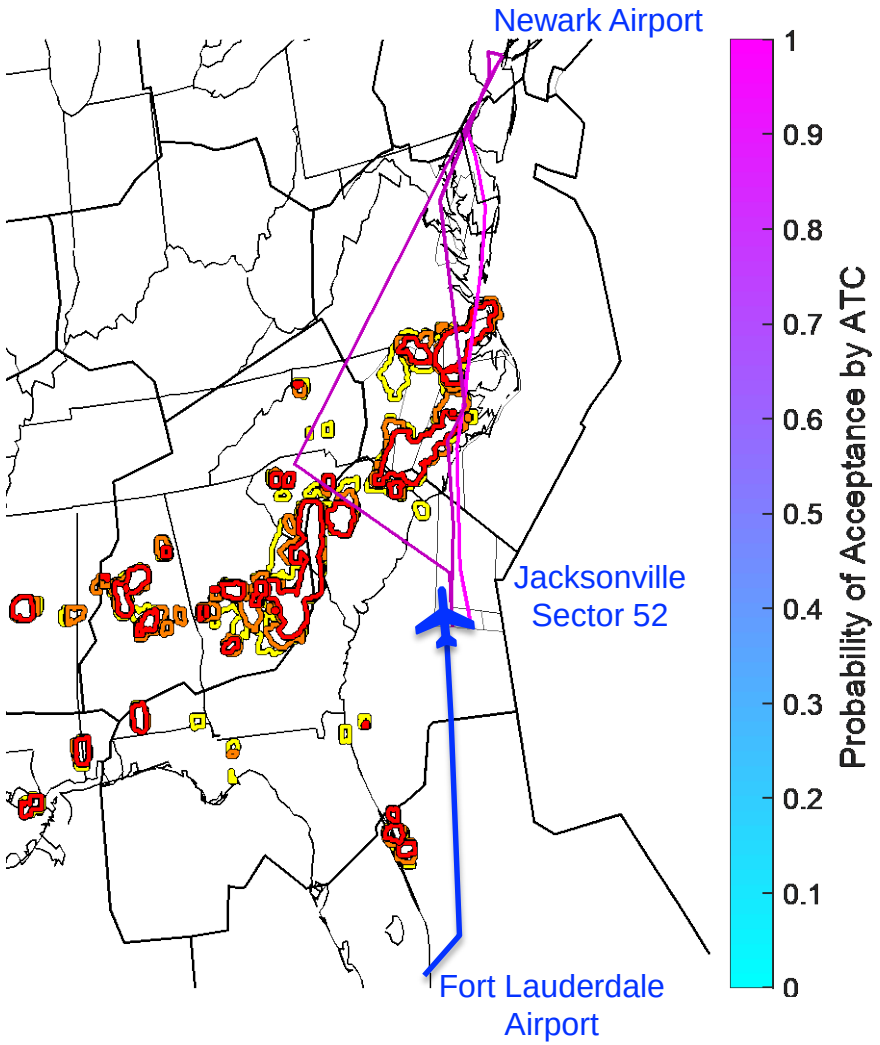
4. Select TOS

- TOS selected based on:
  - Probability of operational acceptance
  - Location of constraint

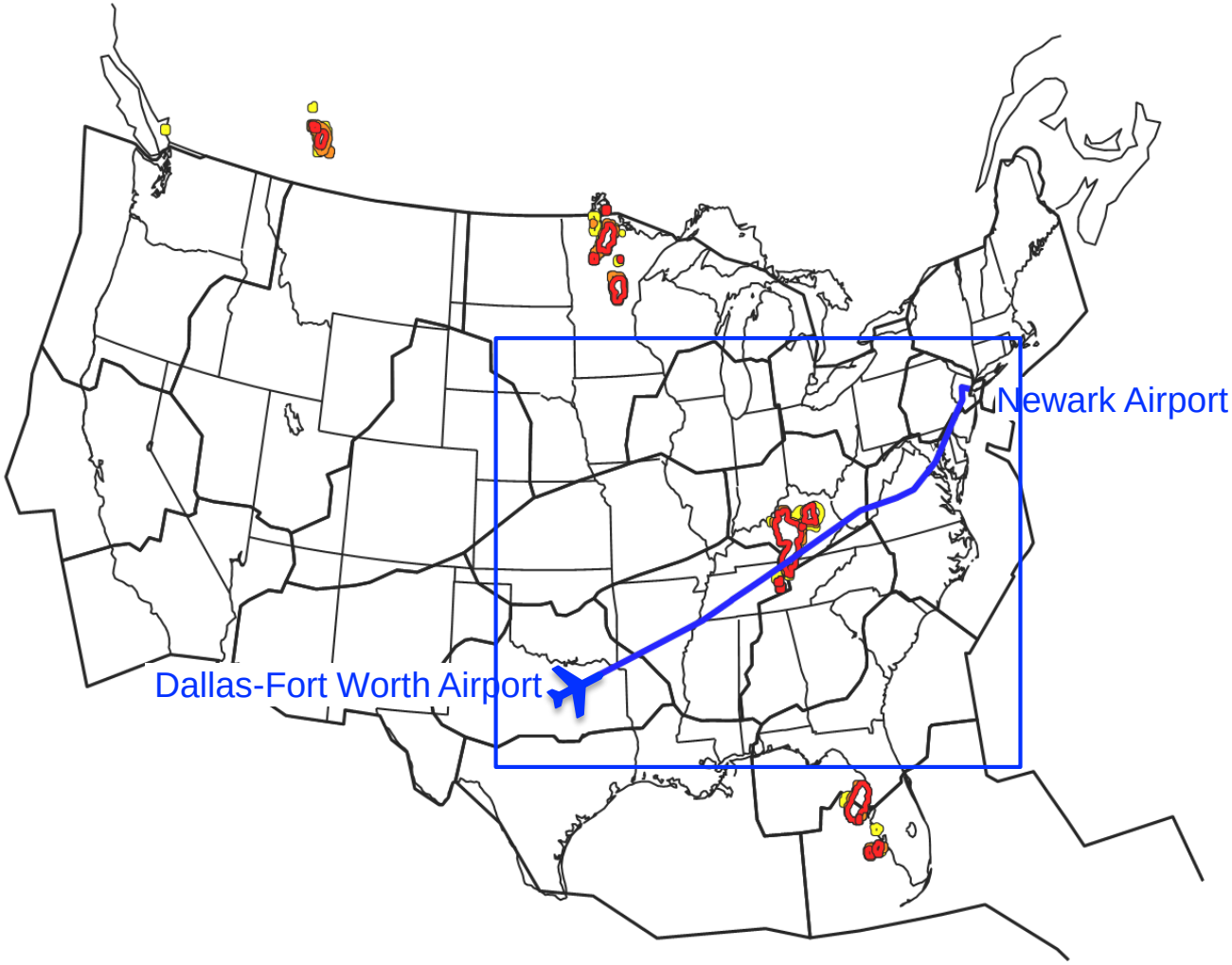


4. Select TOS

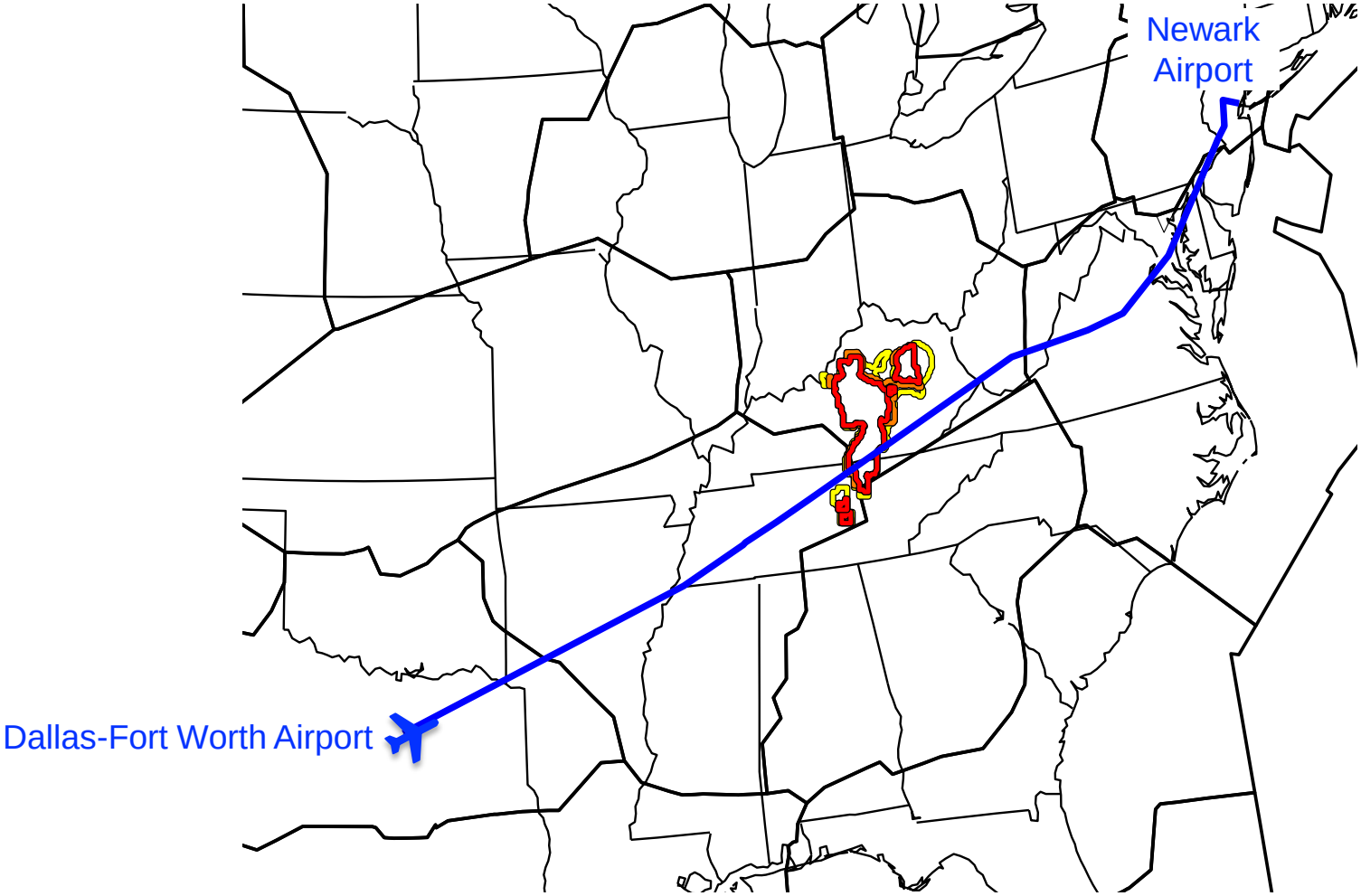
- TOS selected based on:
  - Probability of operational acceptance
  - Location of constraint
- Other factors may also be important
  - Wind optimality
  - Fueling
  - Equipage



Sample Application: Pre-Departure

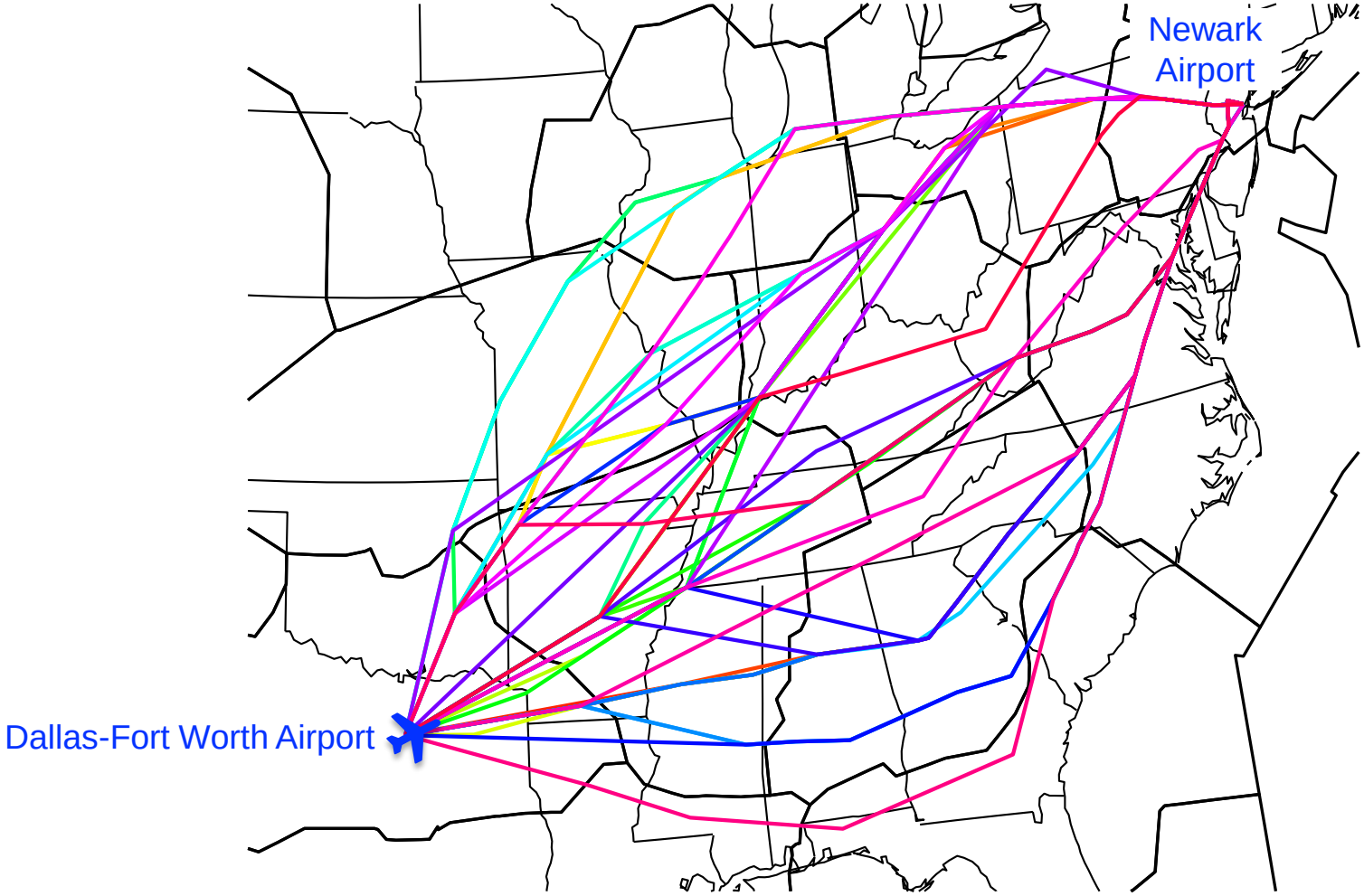


Sample Application: Pre-Departure



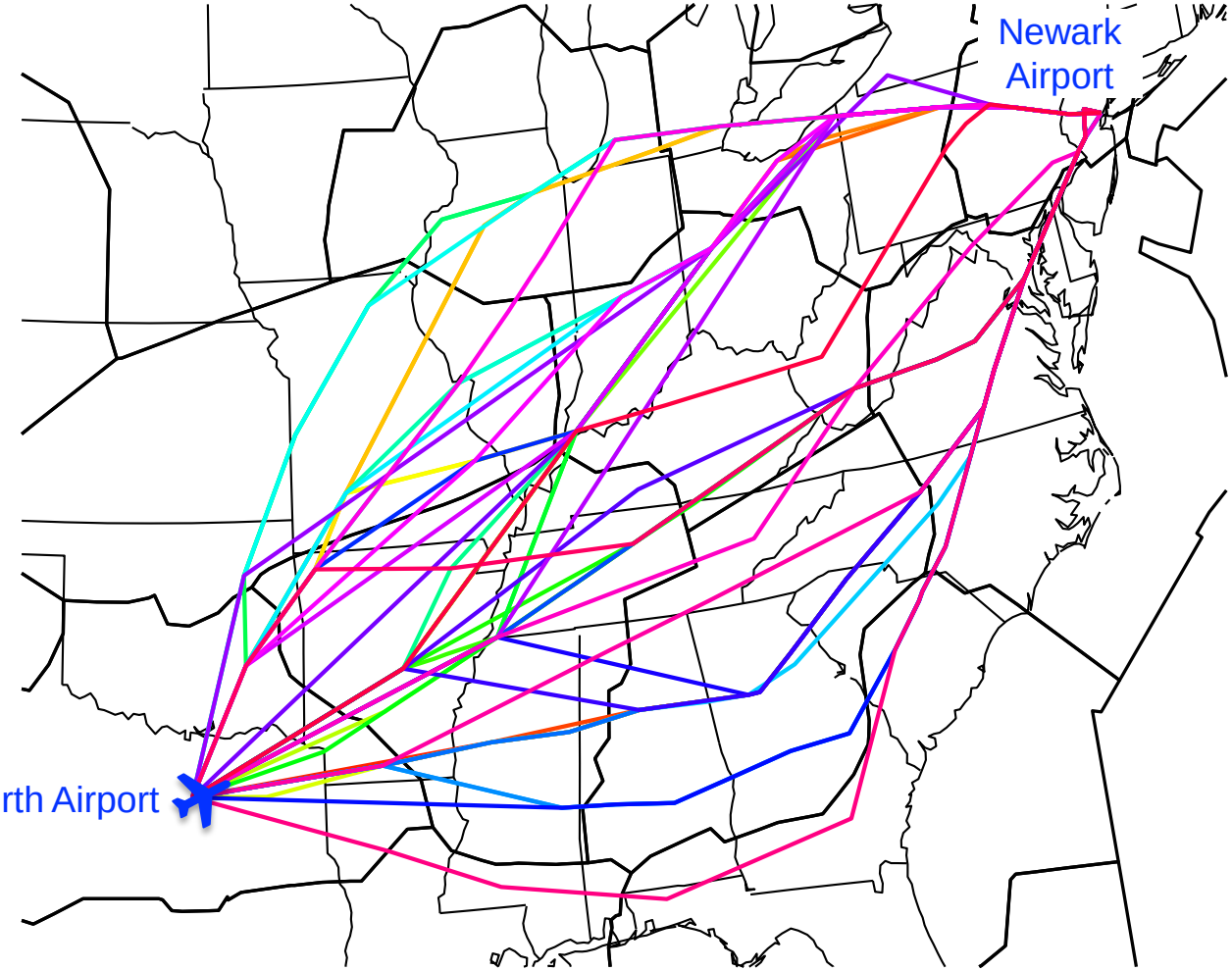
Sample Application: Pre-Departure

1. Identify available trajectory options based on historical routes



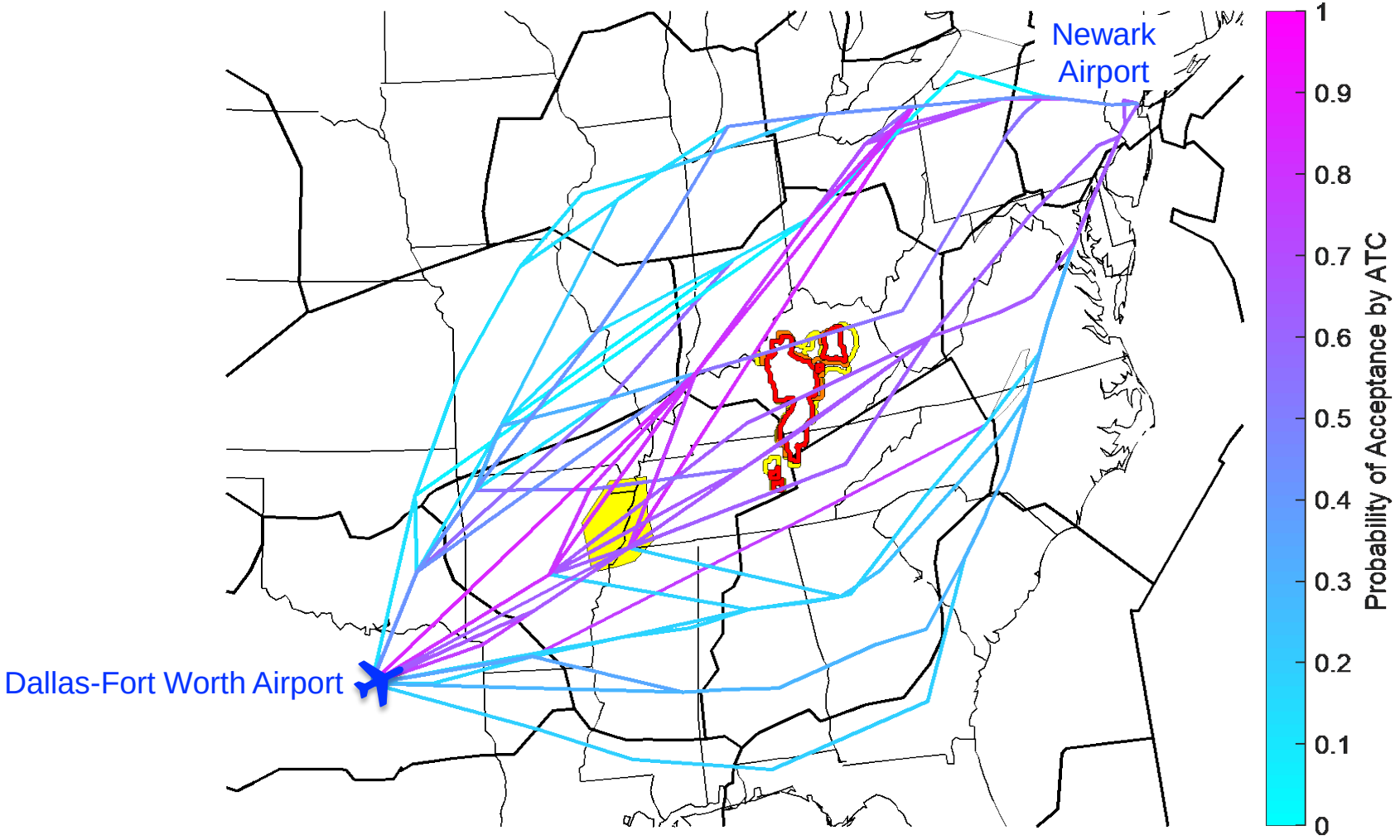
Sample Application: Pre-Departure

2. Down-select trajectory options using clustering



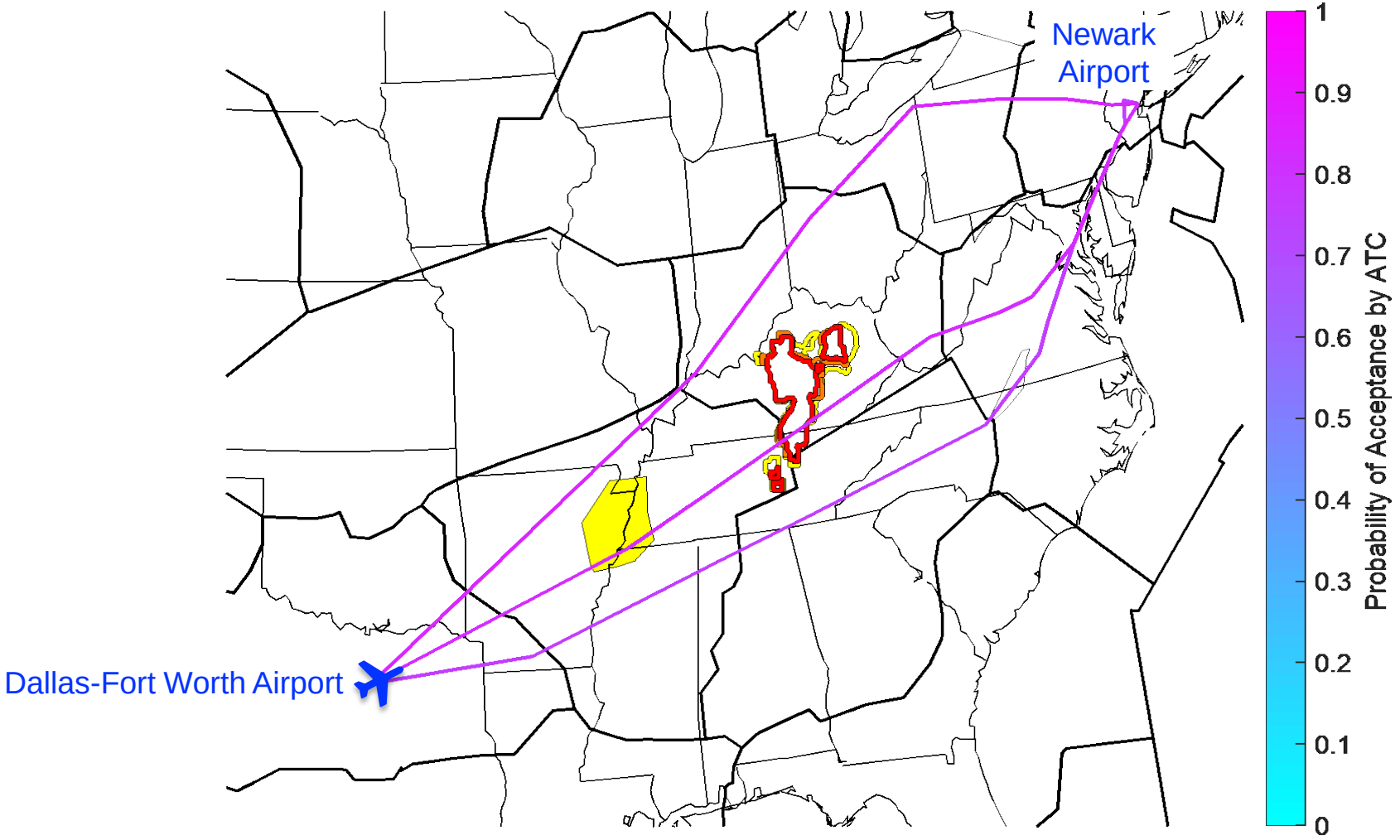
Sample Application: Pre-Departure

3. Predict operational acceptability using machine learning



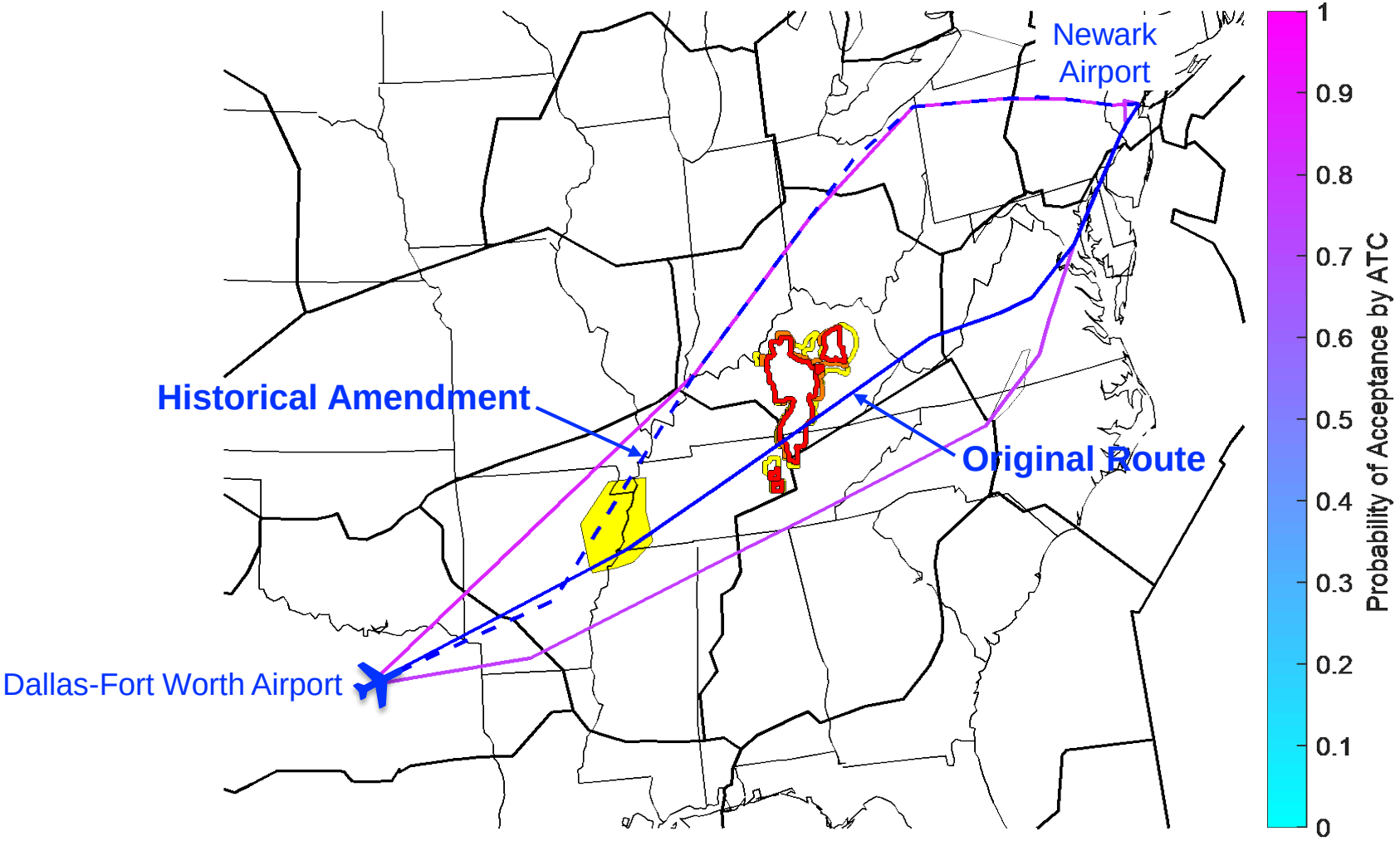
Sample Application: Pre-Departure

4. Select TOS based on operational acceptability and location of constraint



Sample Application: Pre-Departure

4. Select TOS based on operational acceptability and location of constraint



Conclusions

- Machine learning validation results indicate operational acceptability may be predictable with high accuracy
- Approach developed to automatically generate TOSs
  - Incorporated with other capabilities, may be useful in route generation
- Most important features describe difference between amendment and original route for:
  - Flight duration
  - Demand to capacity imbalance
- Could enable more effective trajectory negotiation
  - Could enable flight operators to automatically generate routes with high operational acceptability, and therefore have increased predictability
  - Could enable airlines to effectively submit preferences